

Analysis of Elevation Changes of Pine Island Glacier and Simulation of its Spatial Characteristics

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and

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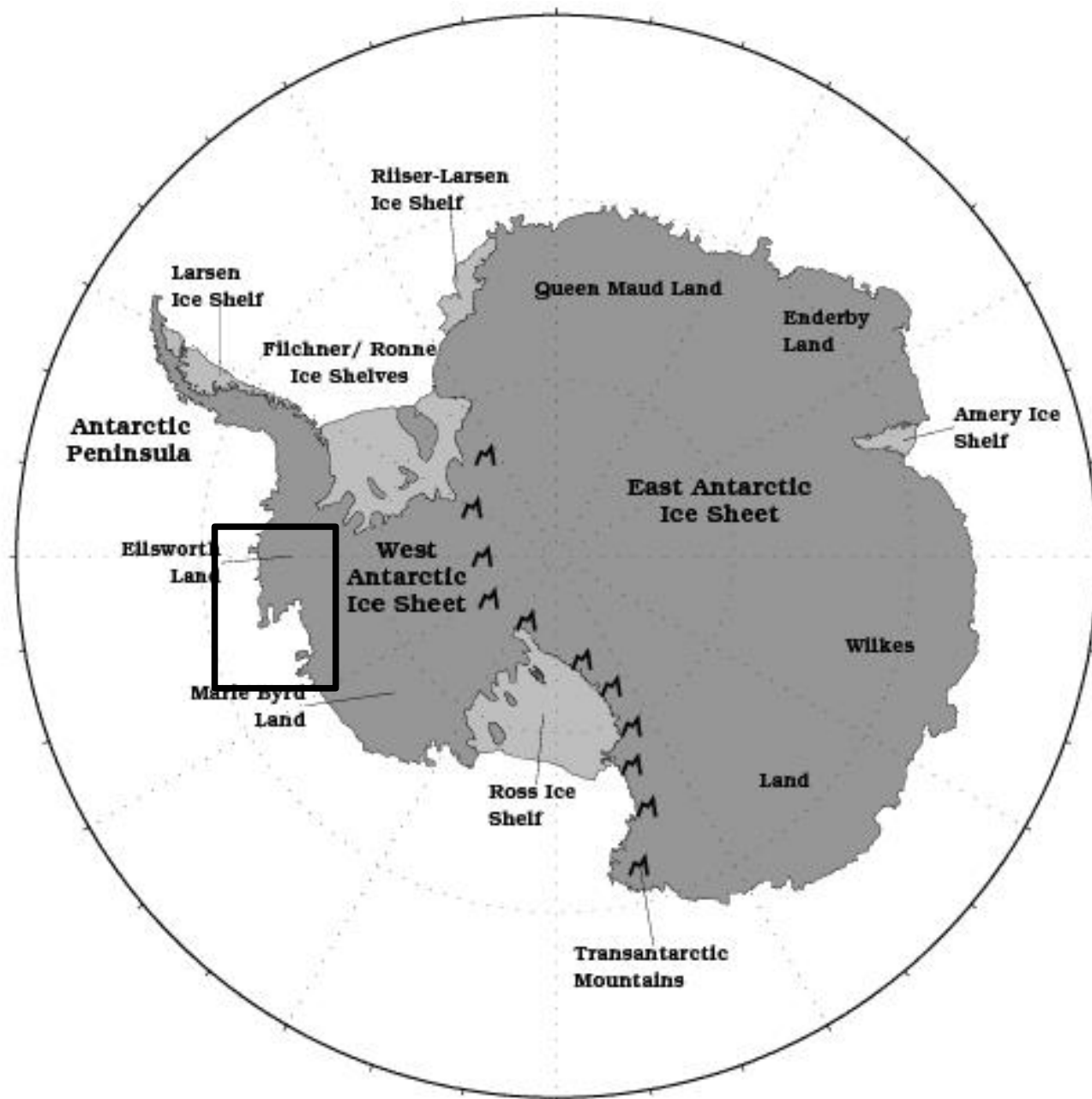
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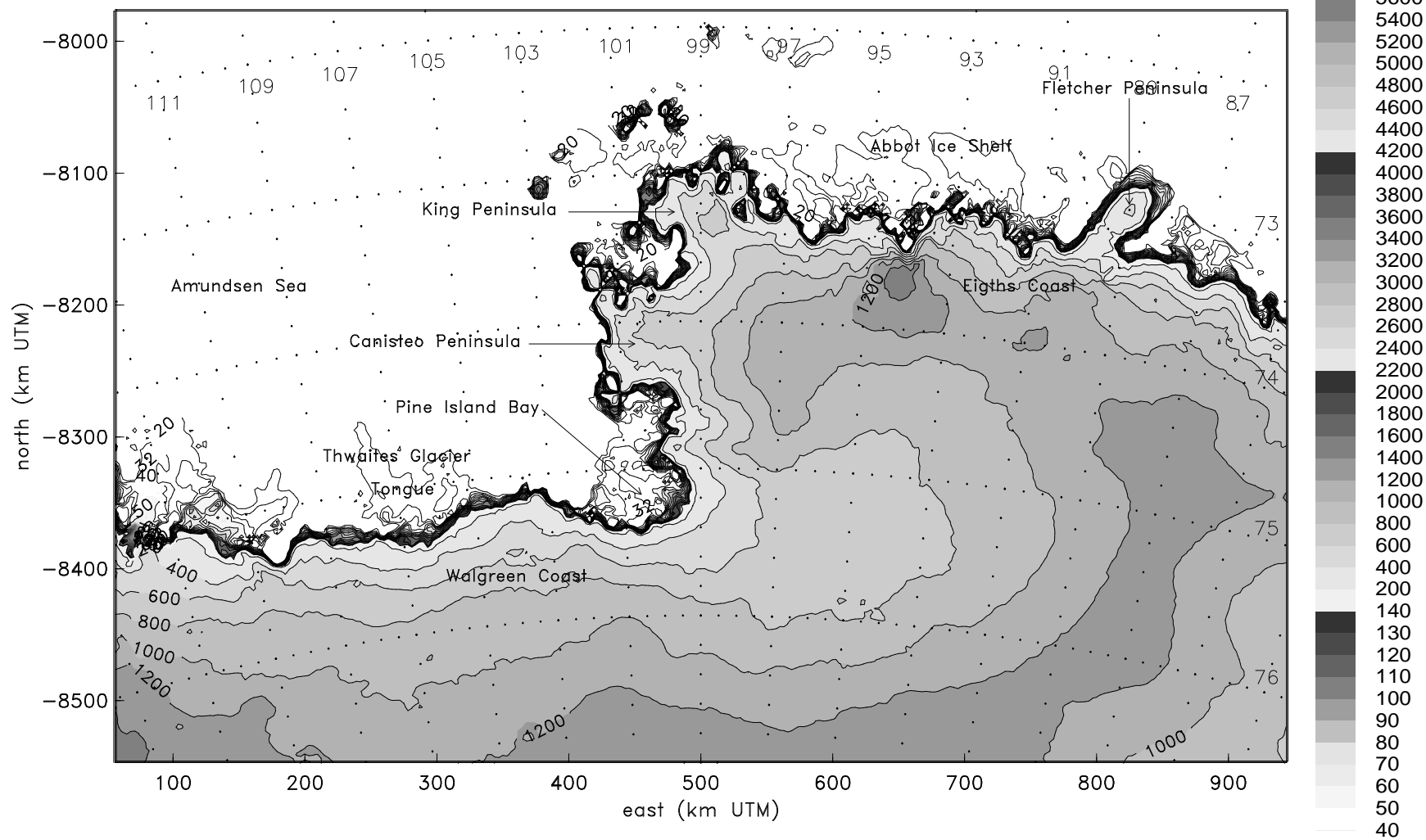
With input from

PatrickMcBricde, Bruce Wallin, Danielle Lirette, Steve Sucht,
Jay Zwally, John DiMarzio

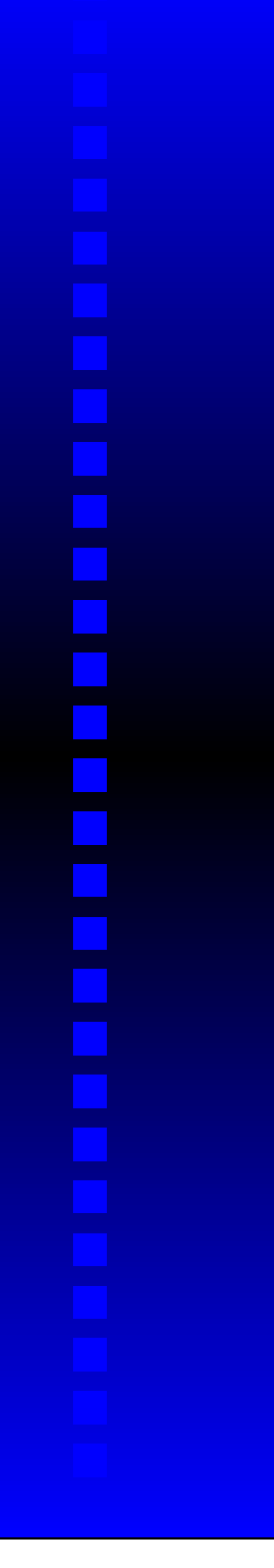
Antarctica with Walgreen Coast (box)



Walgreen Coast – ERS-1 DATA, 1995

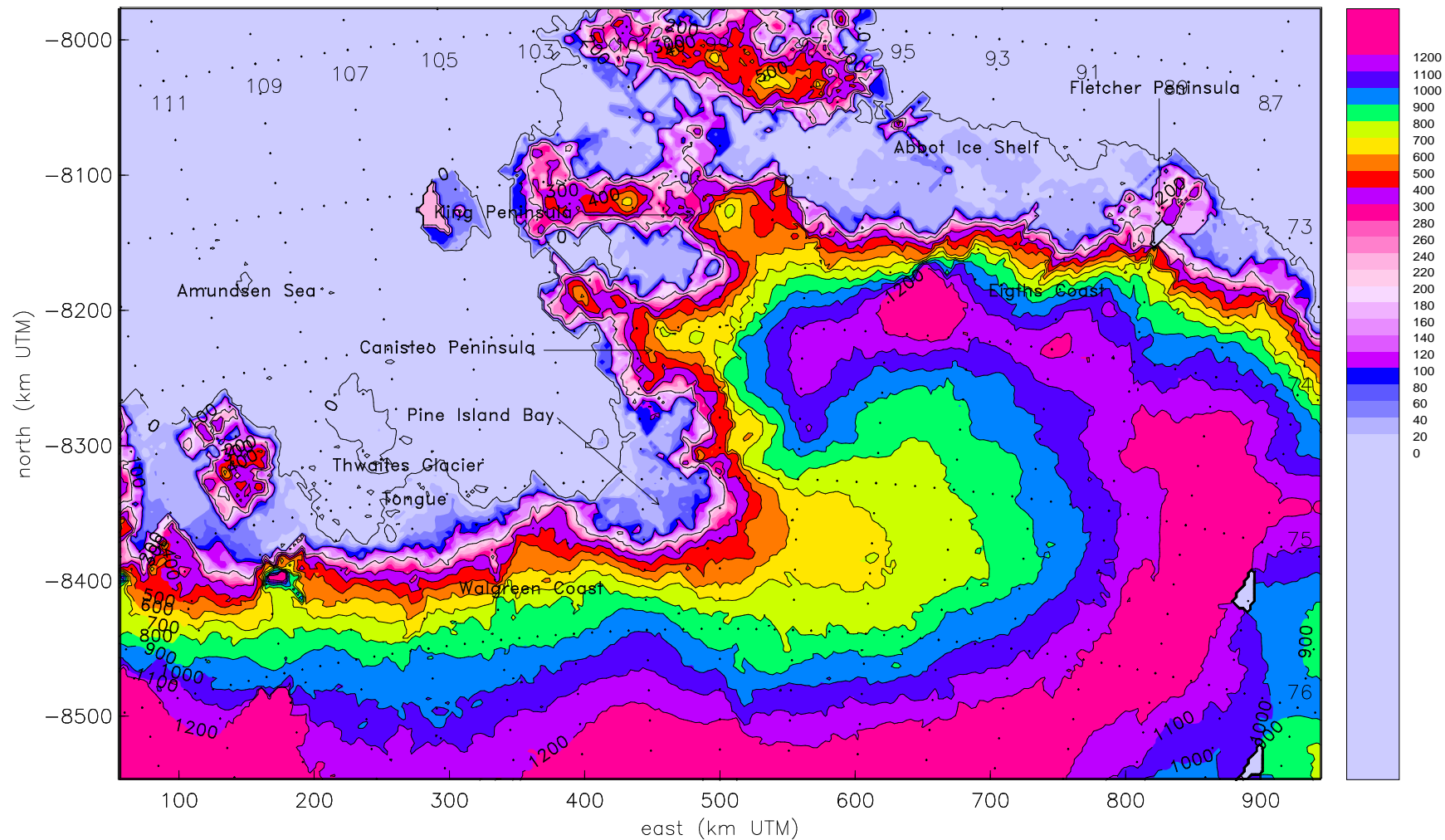


e243-279n71-77, WGS84, Gaussian variog., central mer. 261, slope corrected, scale 1:5000000, 980112



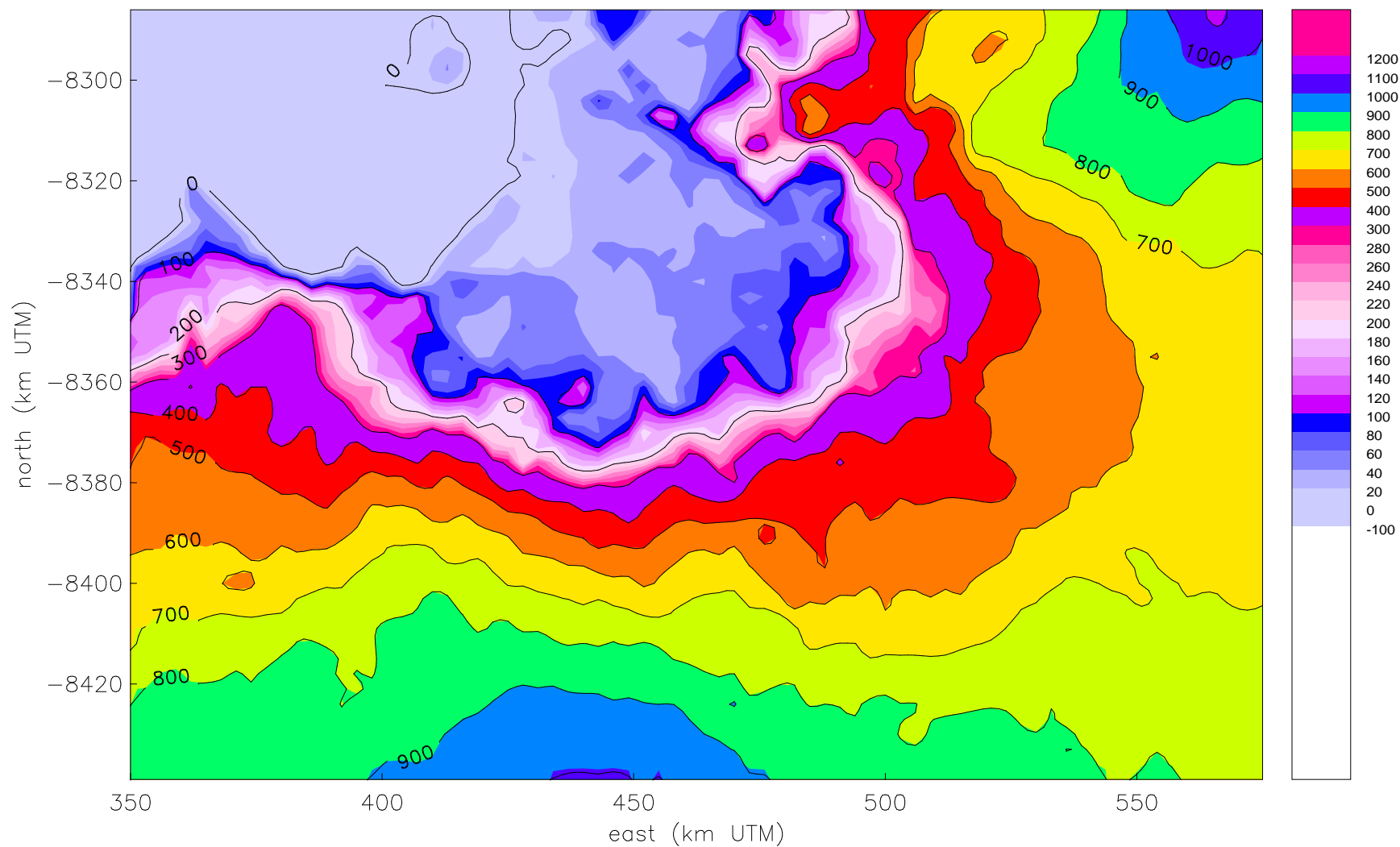
The Role of Pine Island Glacier and Thwaites Glacier in Stability Scenarios for the West-Antarctic Ice Sheet

Walgreen Coast – GLAS Data



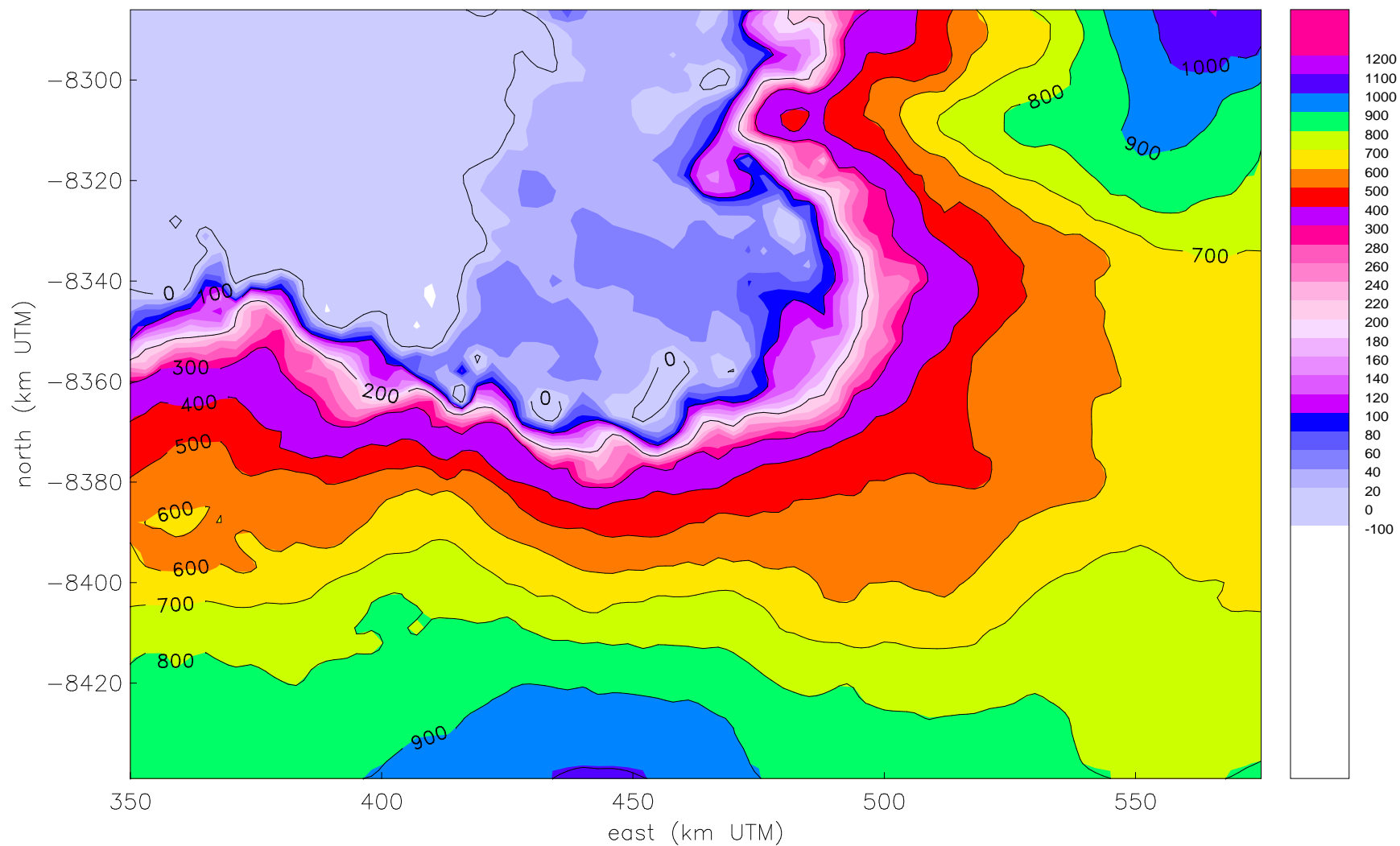
GLA06 Data, (Laser 2A, gain=crit, rel18), Oct/Nov 2003, vario(350,3450,6000m), search=rg 30km, 1:5000000, gla06.1.gain.0.col8

Pine Island Glacier – GLAS Data



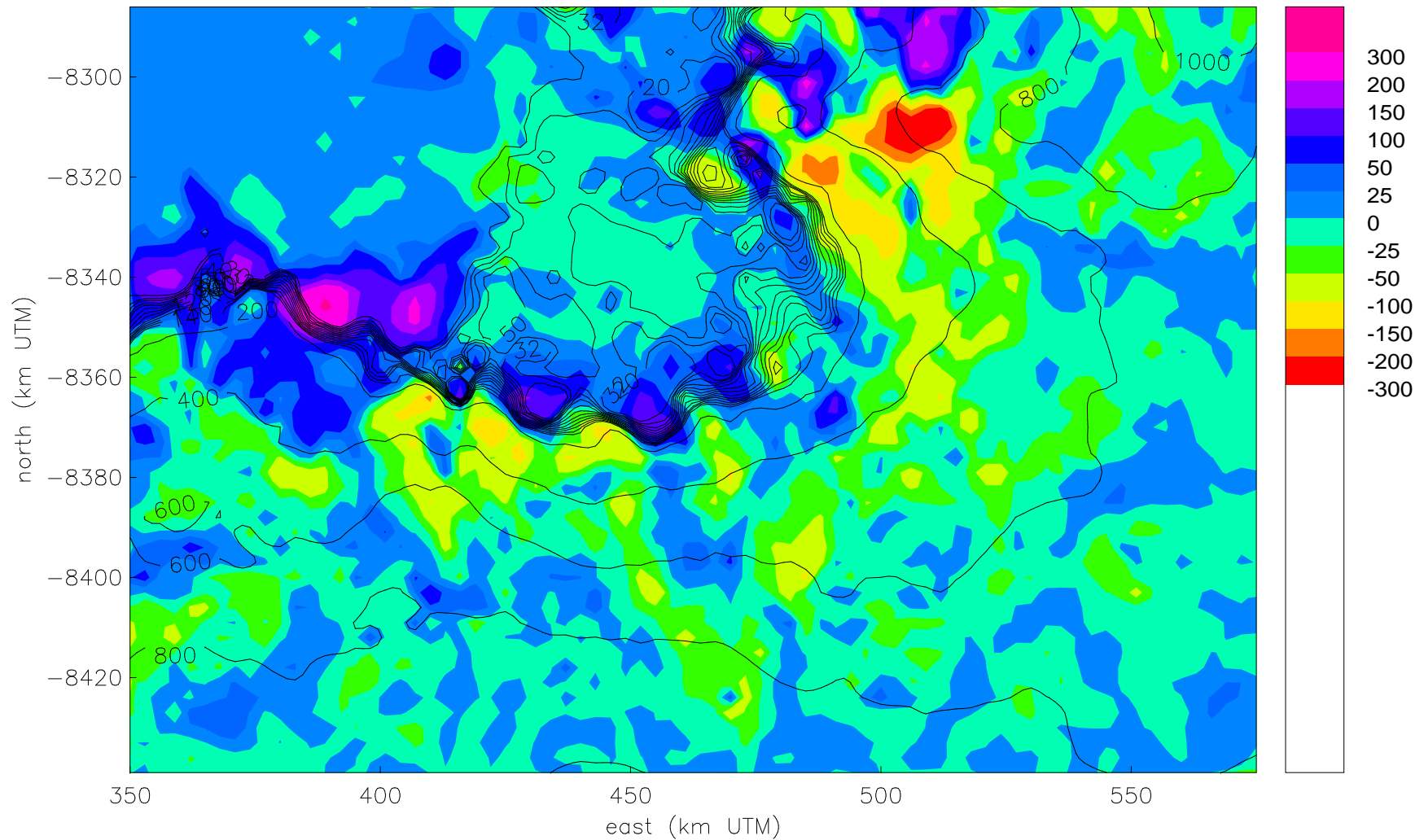
GLA06 Data, (Laser 2A, gain=crit, rel18), Oct/Nov 2003, vario(350,3450,6000m), search=rg
30km, 1:2000000, gla06.1.gain.smallpine2.v2.col8

Pine Island Glacier – ERS-1 Data, 1995



1:2000000, m261e243-279n71-77.e.smallpine2.v2.col8

Pine Island Glacier – GLAS (2003) minus ERS-1 (1995) [with ERS-1 contours]



scale 1:2000000 diff glasgain-ers1.wers1cont.smallpine2.col10.v2.totps 20050404

gla06.1.gain.smallpine2.0.dtm minus m261e243-279n71-77.e.smallpine2.0.dtm

Results:

ICESAt — Pine Island Glacier

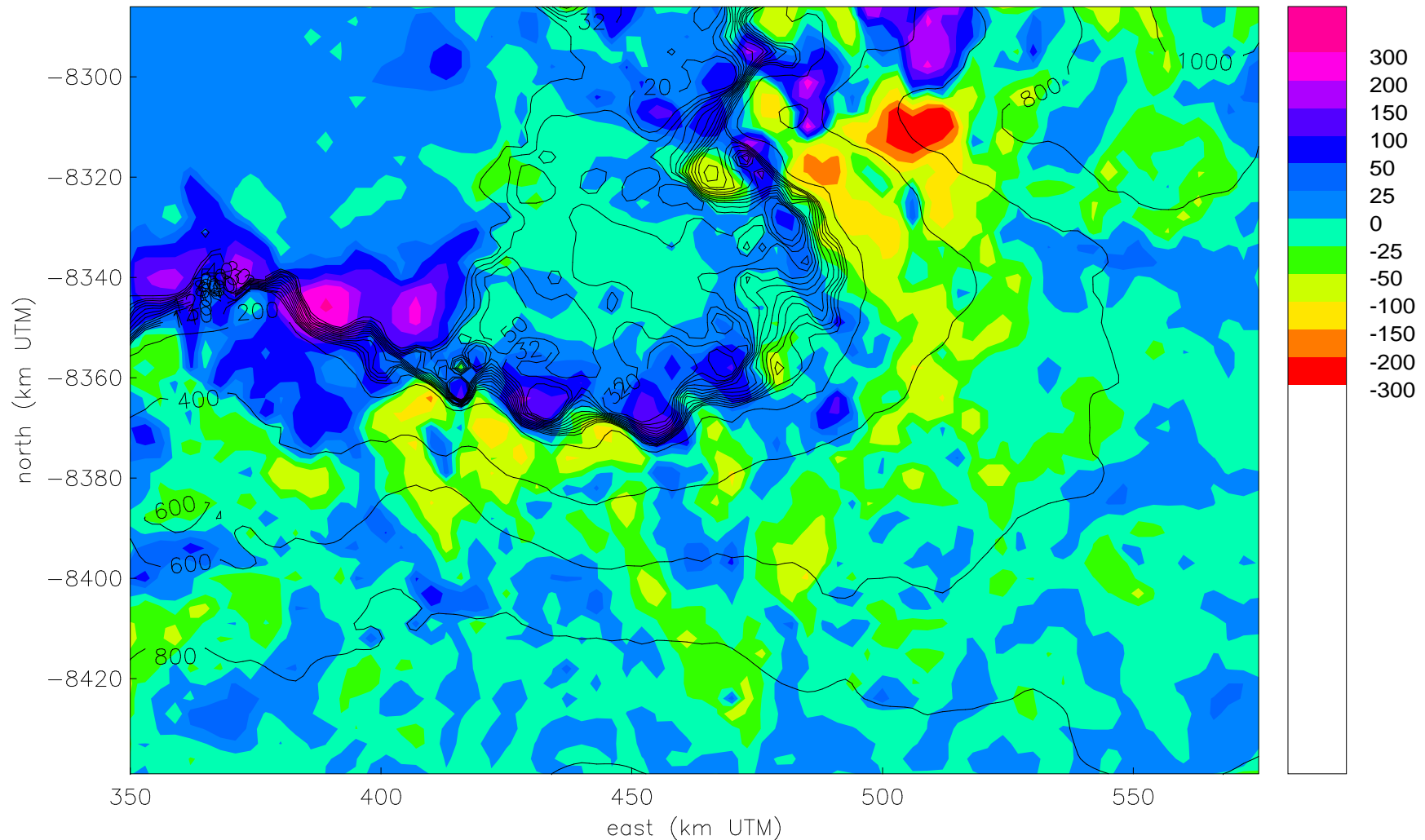
- GLAS measures ice surface altimetry with unprecedented accuracy and precision
- DEMs derived from GLAS data using geostatistical analysis can be utilized for elevation change detection, sufficient for geophysical analysis
- Thinning rates in Pine Island Glacier have been increasing
- The observed retreat of Pine Island Glacier is attributed to internal processes in the glacier, related to dynamic thinning

Herzfeld, McBride, Zwally, DiMarzio, 2008

Does this trend continue?

Change over 8 years: 2005-1995

Pine Island Glacier – GLAS (2003) minus ERS-1 (1995) [with ERS-1 contours]

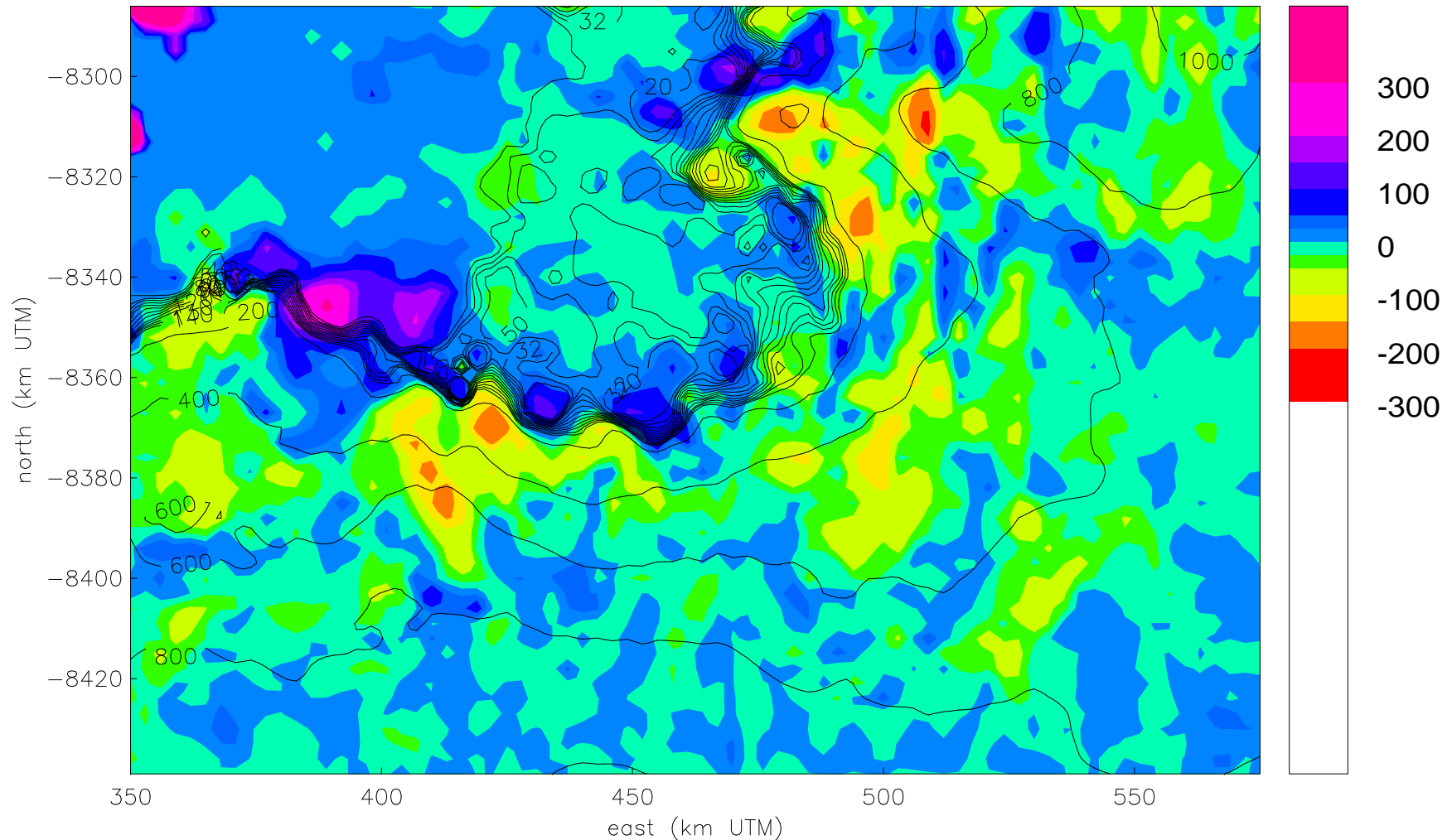


scale 1:2000000 diff glasgain-ers1.wers1cont.smallpine2.col10.v2.totps 20050404

gla06.1.gain.smallpine2.0.dtm minus m261e243-279n71-77.e.smallpine2.0.dtm

Change over 10 years: 2005-1995

Pine Island Glacier – GLAS (2005-05, L3C) minus ERS-1 (1995) [ERS-1 cont]

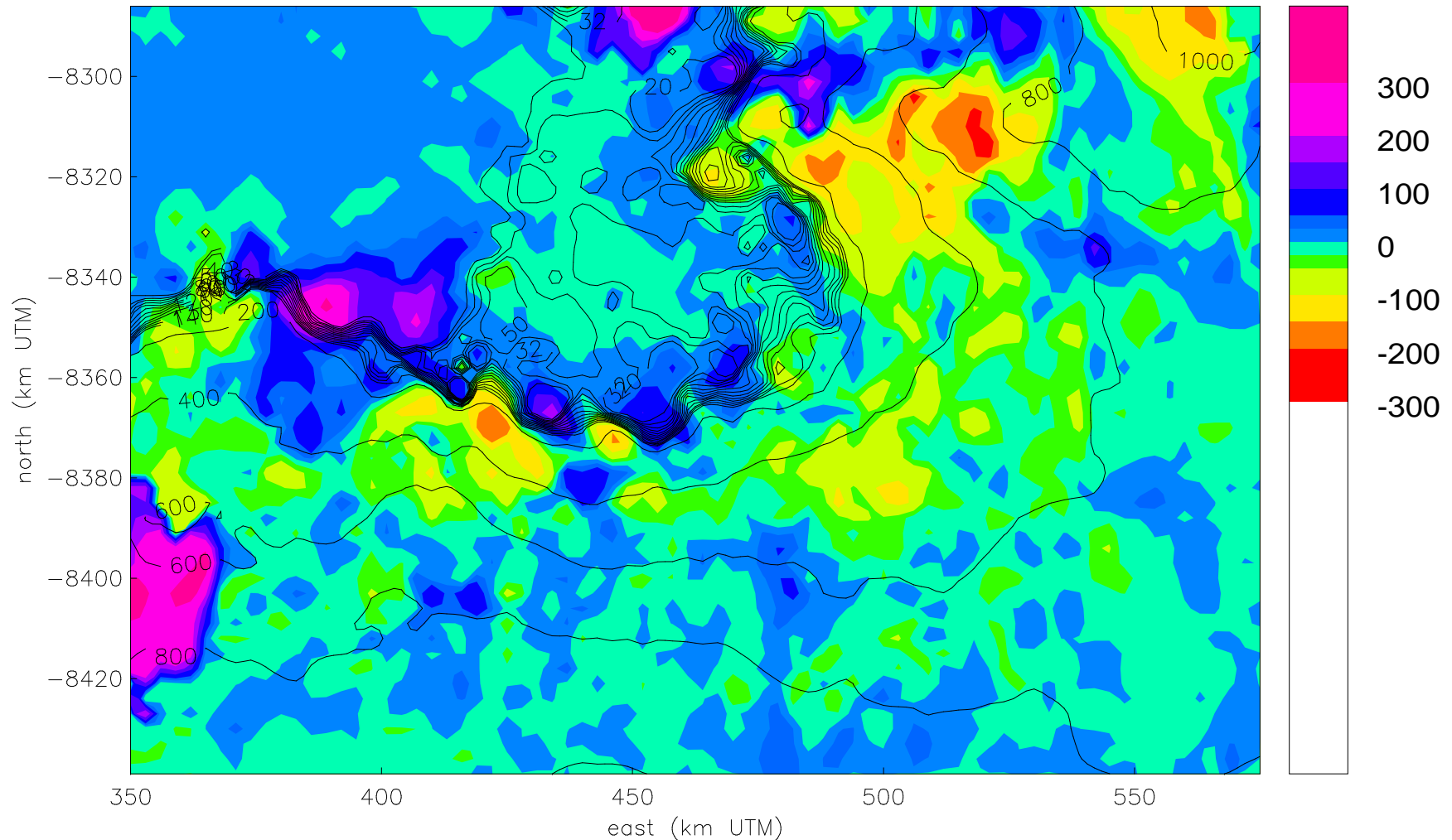


scale 1:2000000 diff.gla12 l3c-ers1.wers1cont.smallpine2.totps 20080927

gla12 rel28 l3c-ers1.dtm (diff.gla12 l3c-ers1.smallpine2.mx)

Change over 11 years 2006 (L3E) -1995

Pine Island Glacier – GLAS (2006-02, L3E) minus ERS-1 (1995) [ERS-1 cont]

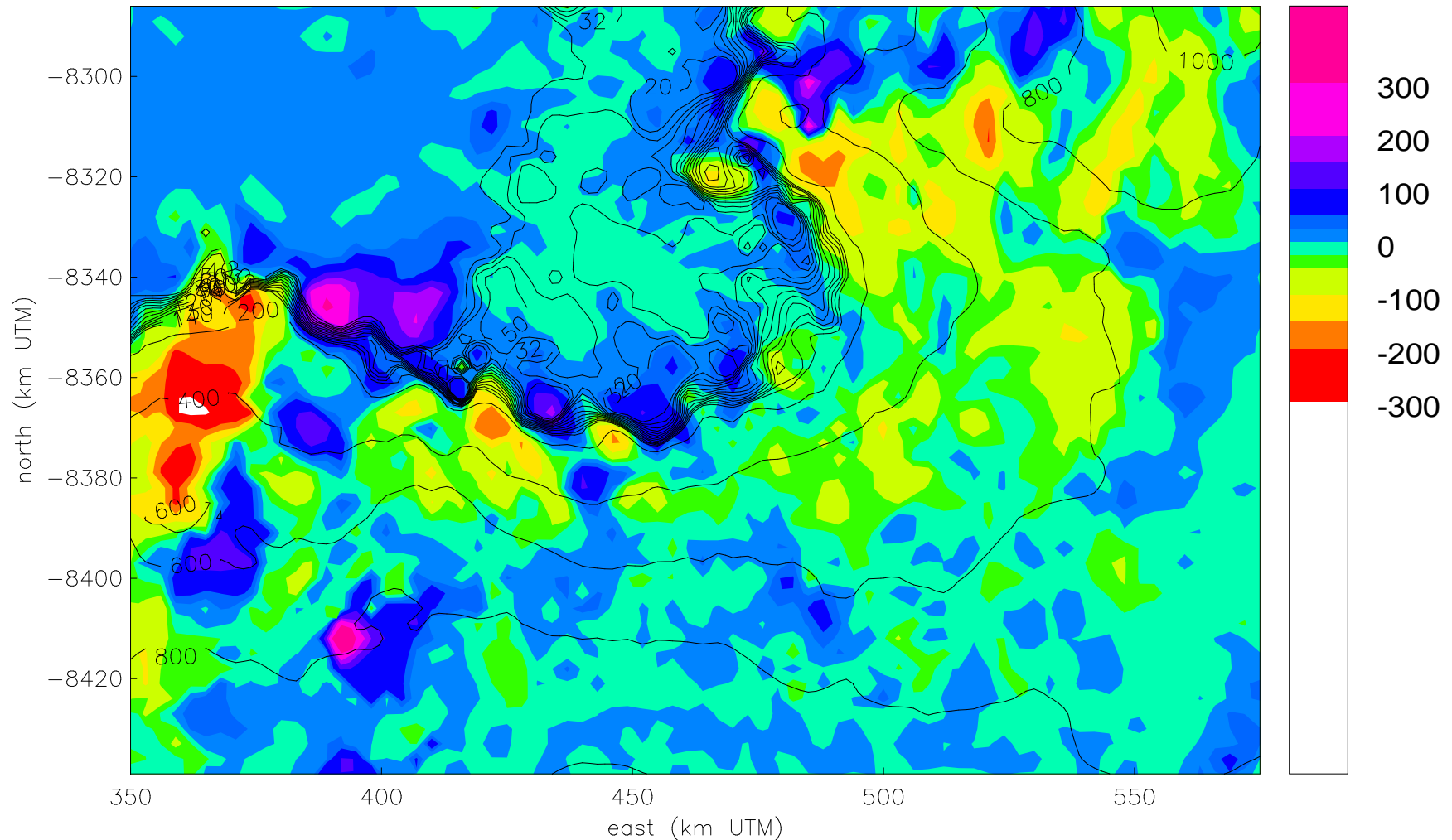


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gla12 rel28 l3e-ers1.dtm (diff.gla12 l3e-ers1.smallpine2.mx)

Change over 11 years 2006 (L3F) -1995

Pine Island Glacier – GLAS (2006-05, L3F) minus ERS-1 (1995) [ERS-1 cont]



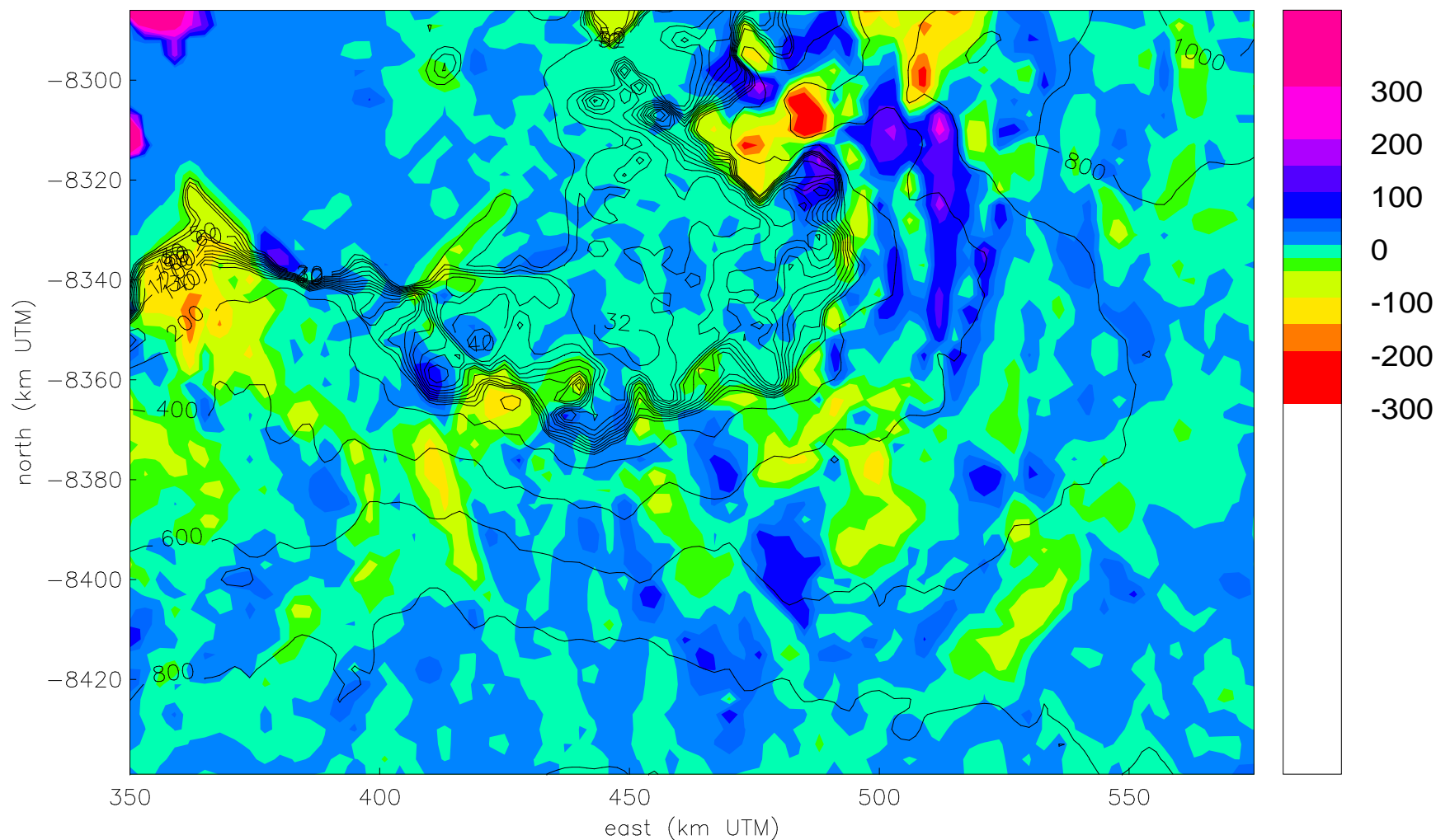
scale 1:2000000 diff.gla12 l3f-ers1.wers1cont.smallpine2.totps 200809027

gla12 rel28 l3f-ers1.dtm (diff.gla12 l3f-ers1.smallpine2.mx)

Change in ICESat years —
Analysis based on GLAS data only

Change over 2 years 2005 (L3C) - 2003 (L2A)

Pine Island Glacier – GLAS (2005-05) minus GLAS (2003-10) [2003 cont]

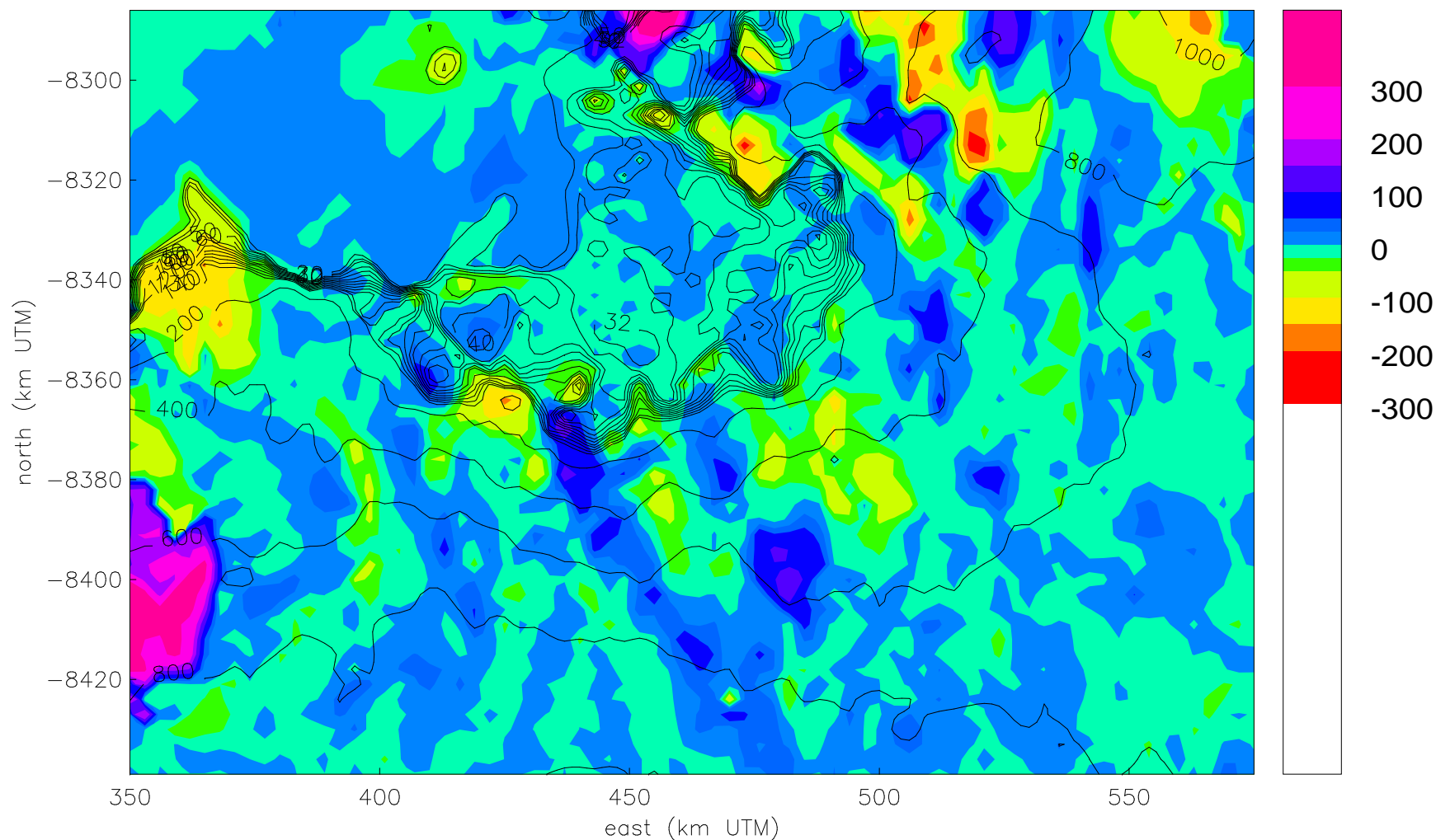


scale 1:2000000 diff.gla12 l3c-l2again.smallpine2.totps 20080927

diff.gla12 l3c-l2again.smallpine2.mx

Change over 3 years 2006 (L3E) - 2003 (L2A)

Pine Island Glacier – GLAS (2006-02) minus GLAS (2003-10) [2003 cont]

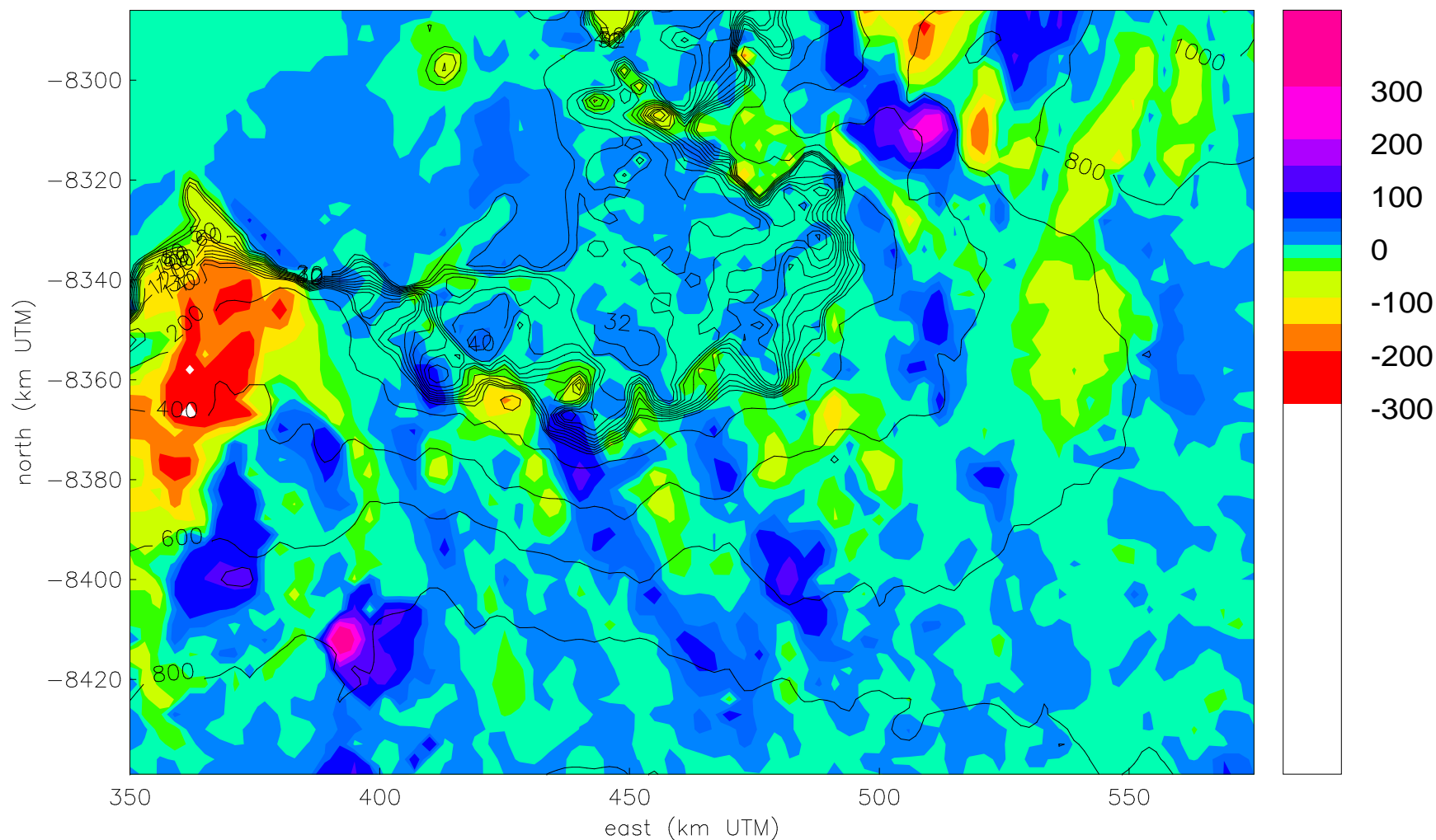


scale 1:2000000 diff.gla12 l3e-l2again.smallpine2.totps 20080927

diff.gla12 l3e-l2again.smallpine2.mx

Change over 3 years 2006 (L3F) - 2003 (L2A)

Pine Island Glacier – GLAS (2006-05) minus GLAS (2003-10) [2003 cont]

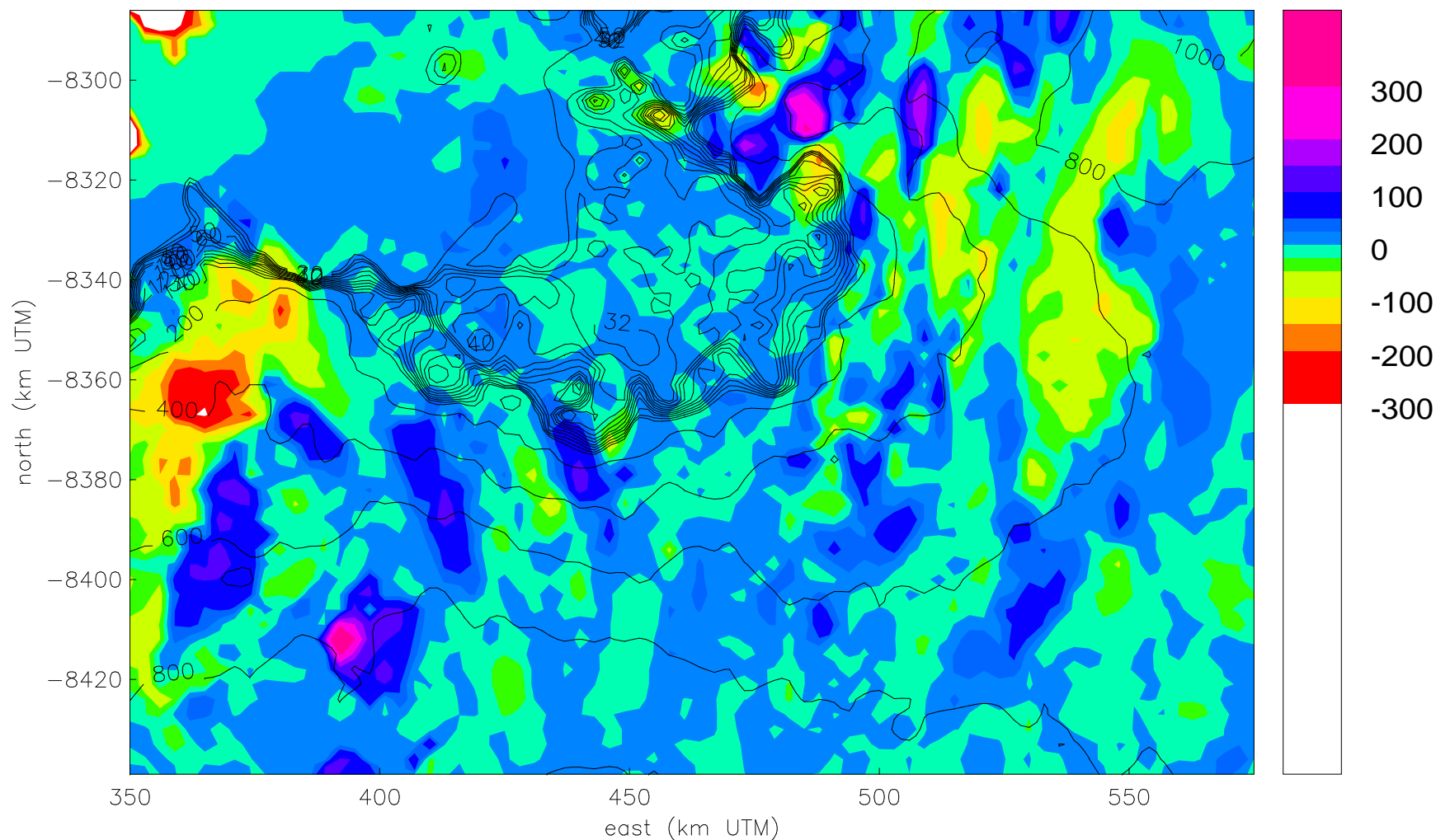


scale 1:2000000 diff.gla12 l3f-l2again.smallpine2.totps 20080927

diff.gla12 l3f-l2again.smallpine2.mx

Change over 1 year 2006-05 (L3F) - 2005-05 (L3E)

Pine Island Glacier – GLAS (2006-05) minus GLAS (2005-05) [2003 cont]

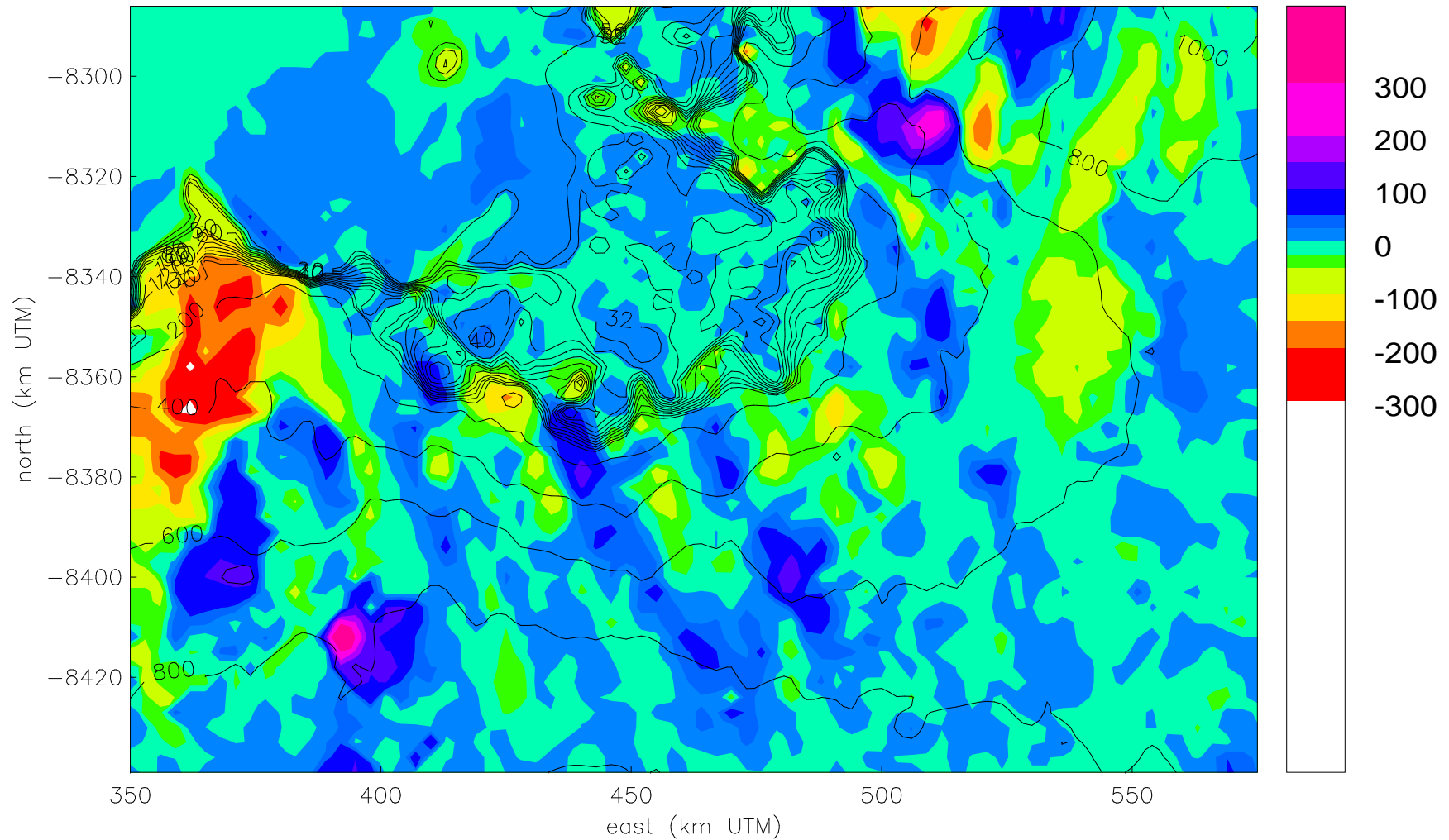


scale 1:2000000 diff.gla12 l3f-l3c.smallpine2.totps 20080927

diff.gla12 l3f-l3c.smallpine2.mx

Seasonal Signal 2006-05 (L3F) - 2006-02 (L3E)

Pine Island Glacier – GLAS (2006-05) minus GLAS (2003-10) [2003 cont]



scale 1:2000000 diff.gla12 l3f-l2again.smallpine2.totps 20080927

diff.gla12 l3f-l2again.smallpine2.mx

Conditional Simulation:

Scale-dependent fractal fields
with natural roughness at every scale

Role of Surface Roughness

To assess the potential of a multi-beam channel to measure high-resolution topography, we need information on **spatial subscale roughness** (ice surface roughness at a resolution higher than that of GLAS observations).

What is spatial surface roughness?

- a derivative of (micro)topography
→ characterization of spatial behavior

(3.) How do we measure surface roughness? — The GRS !



Remote Sensing of Ice Surfaces

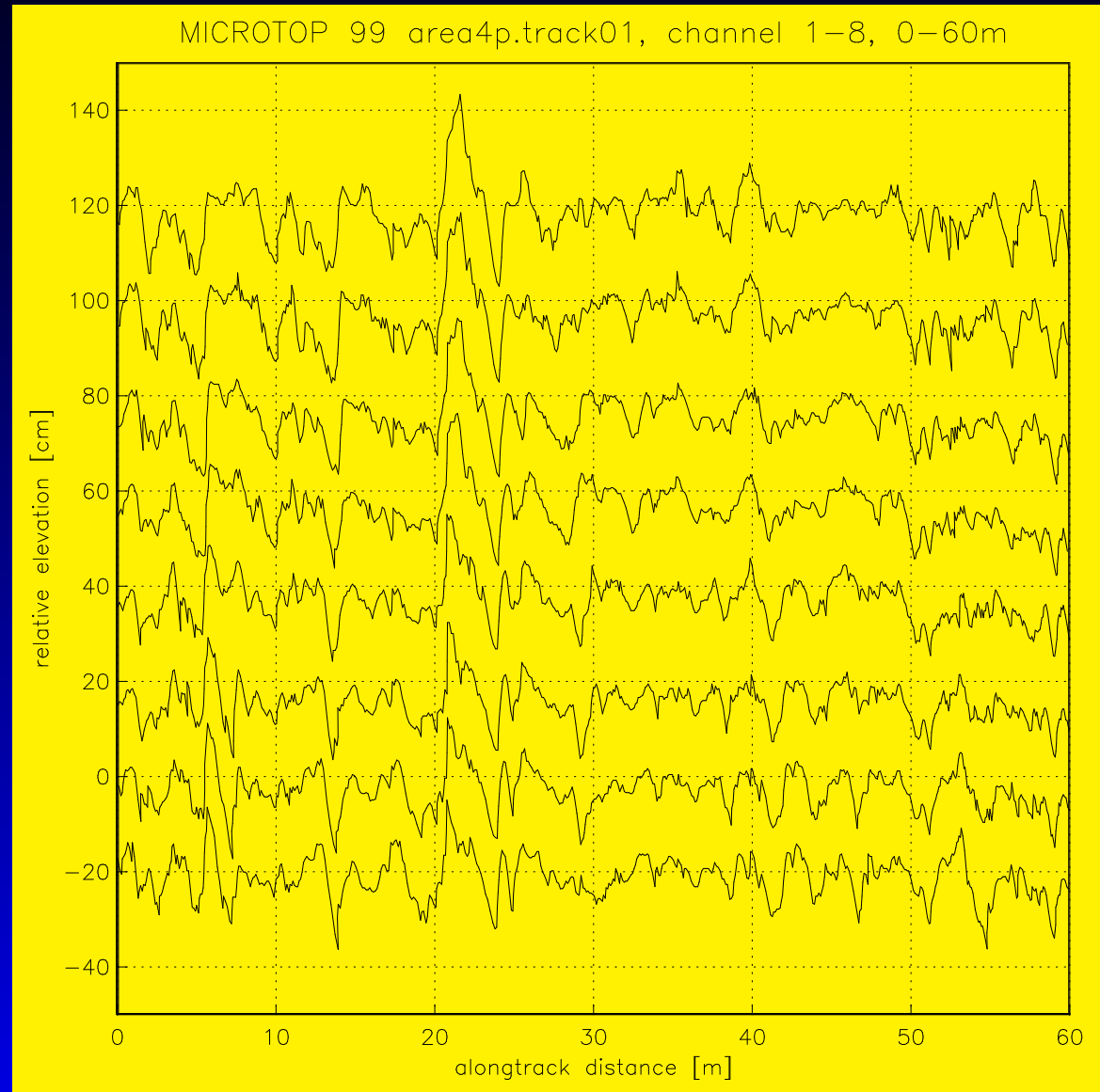
Data	Scales of Resolution
Radar Altimetry	3 km grids
MISR	275 m or 1,000 m pixels
SAR	12.5 m pixels
ATM	7 m resolution
Videography	Submeter resolution

The missing scale

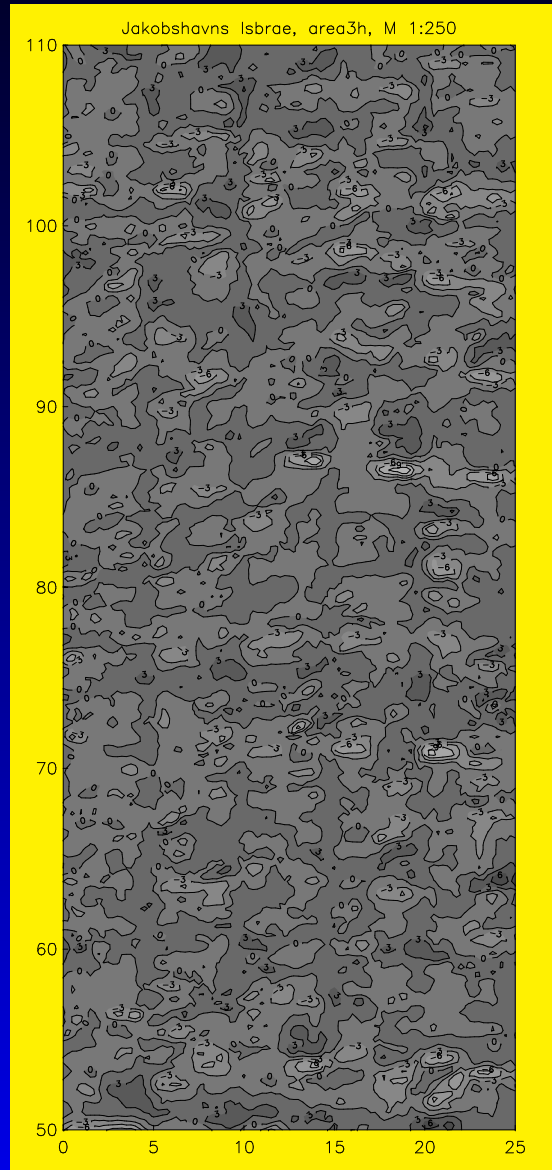
THE GRS	0.2 m resolution
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Material properties	Microscopic scale
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GRS Data – Greenland Ice Sheet



GRS Data – Roughness Model



GRS Data

- data in 8 or 16 channels with across-track resolution 0.2 m
- along-track resolution ≈ 0.1 m
- subcentimeter vertical accuracy

DEMs from GRS data

- 0.2m grids
- areas typically 25 m by 200 m to 200 m by 200 m

Approach: Conditional Simulation of Ice Surfaces

- (1) Use GLAS DEMs as low-res boundary conditions
- (2) Use GRS data (from Greenland) to derive spatial surface roughness parameters using vario functions
- (3) Derive SIMSURF model parameters:
 - (a) scale breaks and their resolutions
 - (b) at every scale range:
 - (b.1) fractal dimension
 - (b.2) direction of anisotropy
 - (b.3) anisotropy factor
- (4) Use SIMSURF software (Herzfeld and Overbeck) to generate ice surface
- (5) Sample model data sets for SB and MB data
- (6) Analyze model data sets

The SIMFRACT method for simulation of scale-dependent fractal surfaces with natural roughness at each scale

(A) Data analysis part

- (1) Calculate scale-dependent dimensions (a - Variogram method, b - Fourier method, c - Isarithm method)
- (2) Determine homogeneity ranges of scale
- (3) Determine anisotropies at each scale range

(B) Simulation part

- (4) Set up a simulation network, matching scale breaks
- (5) Decide on scale ranges to interpolate versus ranges to simulate
- (6) Select interpolation method (Shephard, 4-pt)
- (7) Select simulation method (conditional, unconditional; using Fourier filter method for uncondl simulation of scale-dependent Fractional Brownian surfaces)
- (8) Select a method to merge scales

Variogram method for function graphs

PROPOSITION 9 (Variogram method for estimation of box dimension of graph of a real function): Let $f : \mathcal{R} \rightarrow \mathcal{R}$ be a continuous and self-affine function. Assume existence of the autocorrelation function C of f . Then there is a real number $c > 0$, such that

$$\gamma(h) = C(0) - C(h) \approx c h^{4-2s} \quad (22)$$

and $\dim_B(\text{graph } f) = s$.

If Hoelder conditions are satisfied, the box dimension of f may be calculated according to

$$\dim_B(\text{graph } f) = s \approx 2 - \frac{1}{2} \frac{\log(\gamma(h))}{\log(h)} + \frac{c}{\log(h)} \approx 2 - \frac{1}{2} \lim_{h \rightarrow 0} \frac{\log(\gamma(h))}{\log(h)} \quad (23)$$

which may be estimated using linear regression.

Variogram method in \mathcal{R}^3

REMARK 10 (Variogram method for estimation of box dimension for surfaces in \mathcal{R}^3): Let $(x, y) \in \mathcal{D} \subseteq \mathcal{R}^2$, $f : \mathcal{D} \rightarrow \mathcal{R}$ an (elevation) function, and $\mathcal{S} = \{(x, y, z) | (x, y) \in \mathcal{D} \text{ and } z = f(x, y)\}$. Let $d : \mathcal{R}^2 \rightarrow \mathcal{R}$ denote distance according to the L_2 -norm. Assume $\dim_B(\mathcal{S}) = \dim_B(\mathcal{S} \cap \mathcal{T}) + 1$ for each intersection $\emptyset \neq \mathcal{S} \cap \mathcal{T}$ with a plane \mathcal{T} , and assume that the restriction $f|_{\mathcal{S} \cap \mathcal{T}}$ satisfies all the conditions of Propositions 8 and 9 above. Then the following approximations hold:

$$\gamma(d(h)) = C(0) - C(d(h)) \approx cd(h)^{6-2s} \quad (24)$$

and

$$\dim_B(\mathcal{S}) \approx 3 - \frac{1}{2} \lim_{d(h) \rightarrow 0} \frac{\log(\gamma(d(h)))}{\log(d(h))} \quad (25)$$

which may be estimated using linear regression.

Wiener-Kinchine Theorem

The Wiener-Kinchine theorem states that the power-spectral density is the Fourier transform of the autocorrelation function:

$$C(h) \Rightarrow |\Phi(p)|^2 = E_{SP}[f](p) \quad (32)$$

For two-dimensional functions, the Wiener-Kinchine theorem states that the power-spectral density is the Fourier transform of the covariance function.

Fourier method for function graphs

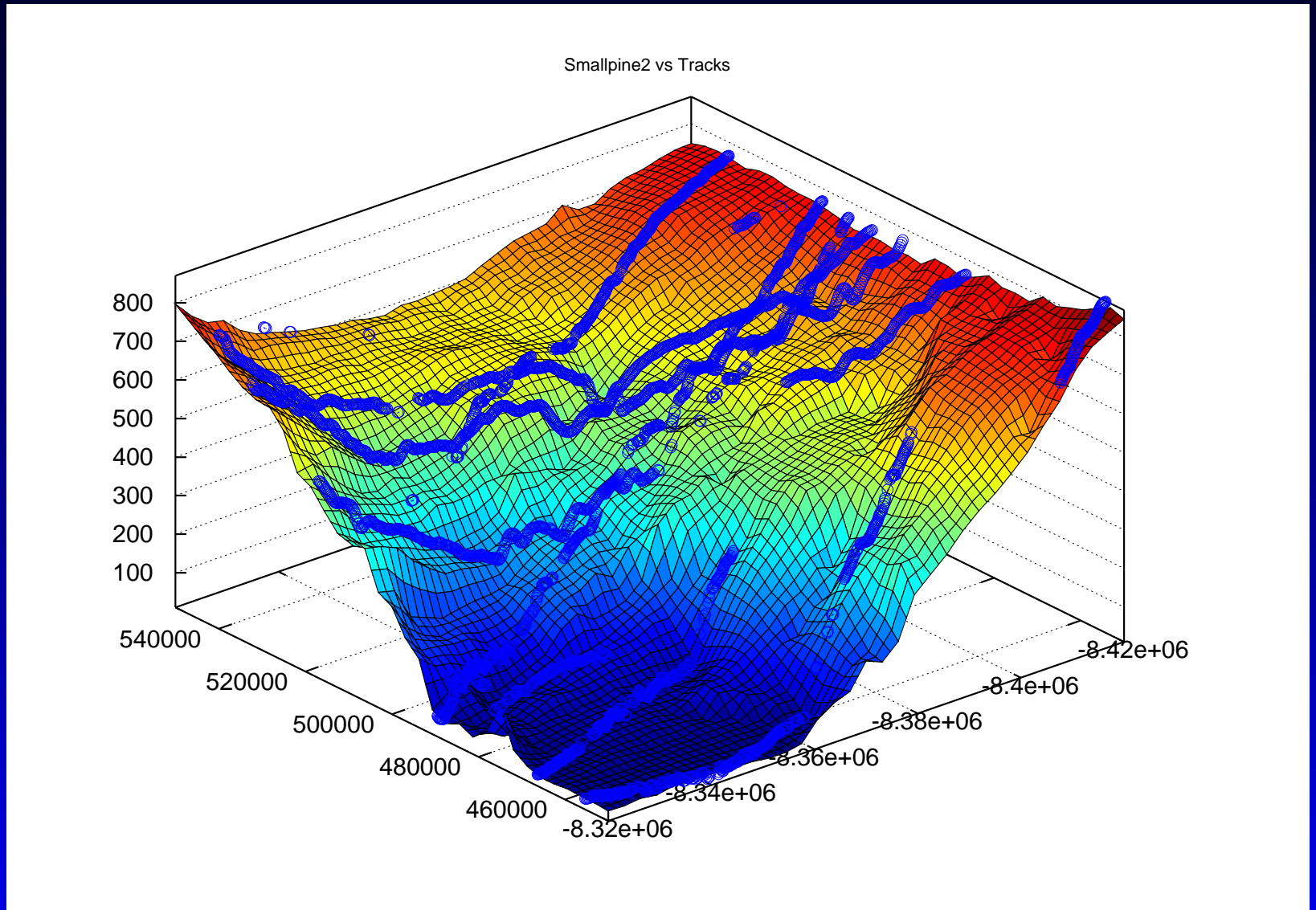
PROPOSITION 11 (Fourier method for calculation of box dimension for graph of a real function): Let $f : \mathcal{R} \rightarrow \mathcal{R}$ be a continuous and self-affine function, assume existence of the autocorrelation function C of f . Let $\Phi(p)$ denote the Fourier transform of f and E_{SP} the power-spectral density. If

$$E_{SP}[f](p) = |\Phi(p)|^2 \sim \frac{1}{p^\beta} \quad \text{for some } \beta \in \mathcal{R}, \quad (33)$$

then

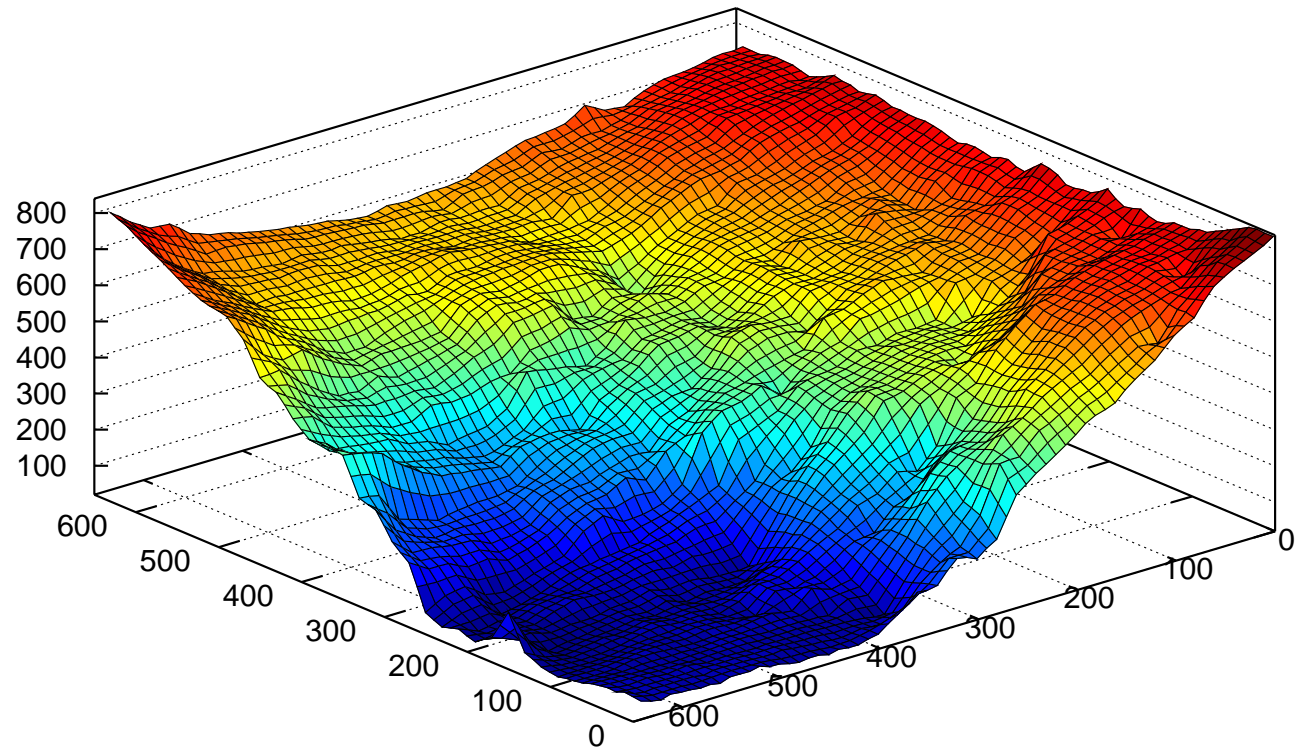
$$\beta \approx 5 - 2\dim_B(\text{graph } f) \quad \text{and} \quad \dim_B(\text{graph } f) \approx \frac{5 - \beta}{2}. \quad (34)$$

Pine Island Glacier — L2A GLAS Data (2003)



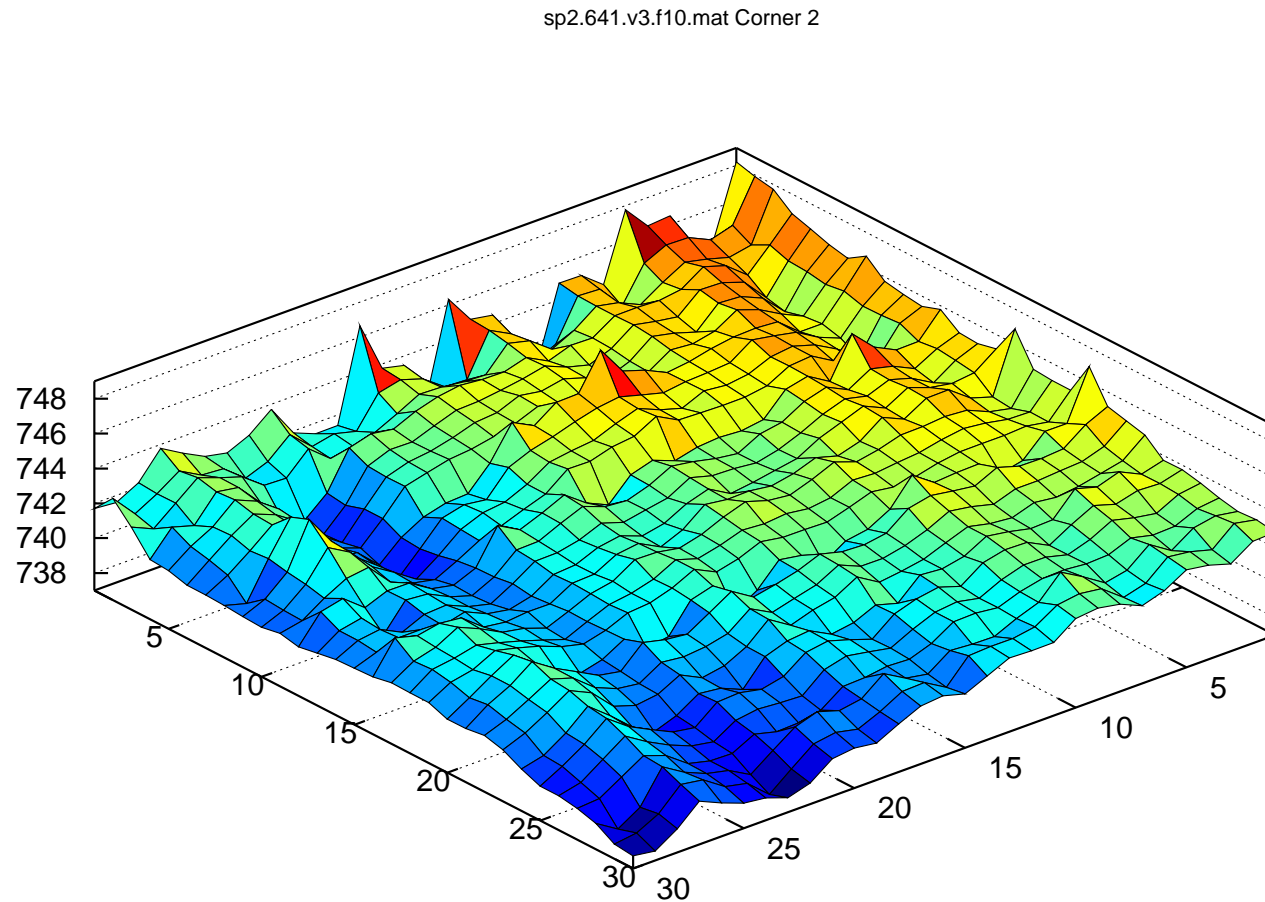
3D view upglacier, based on DEM from GLAS data, with GLAS data locations

Conditional Simulation: Pine Island Glacier

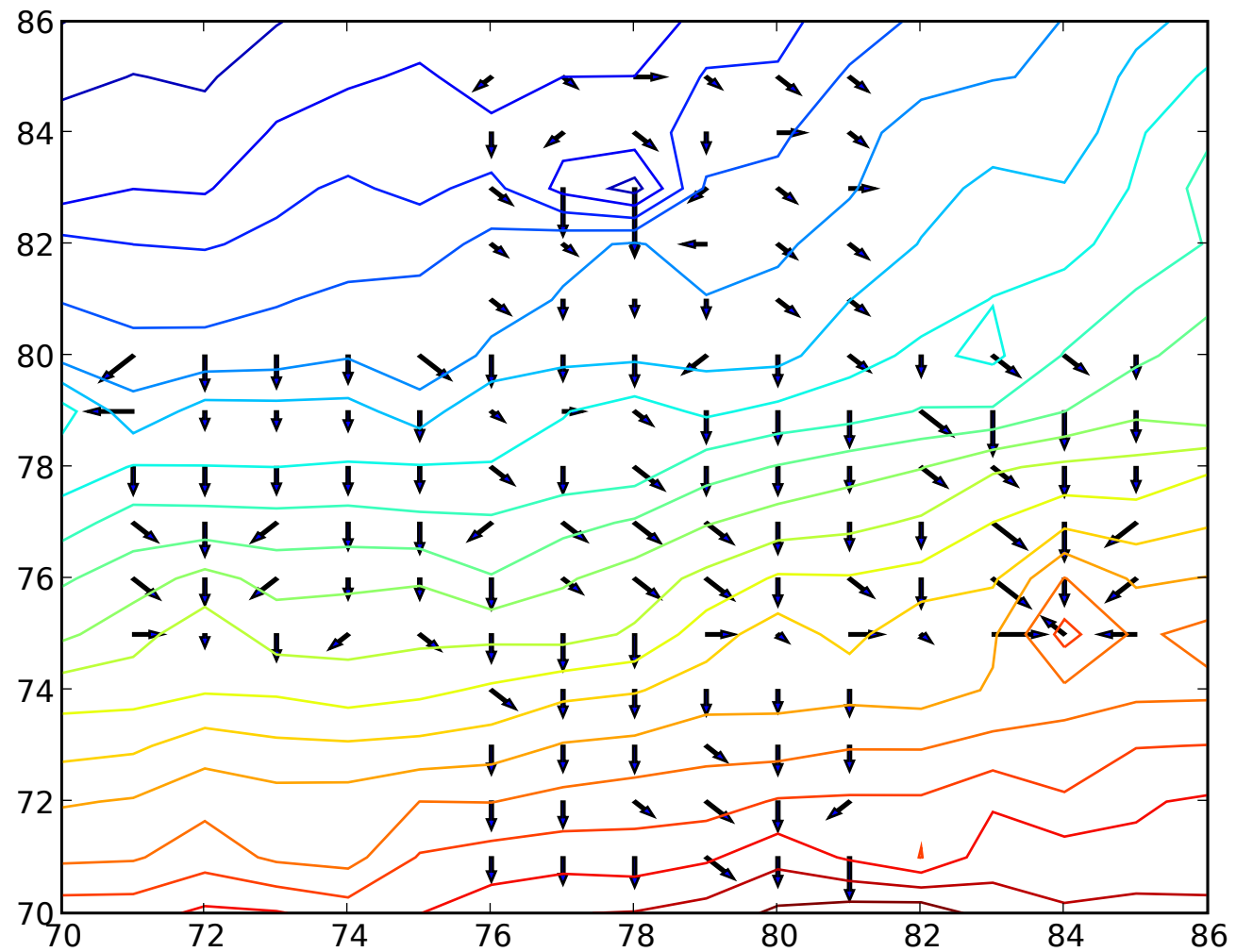


3D view upglacier, based on DEM from L2 (2003) GLAS data

Conditional Simulation: Pine Island Glacier – Enlarged Subarea

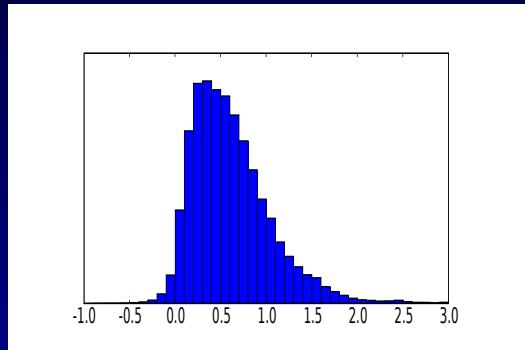


Gradient Map from Multi-Beam Data



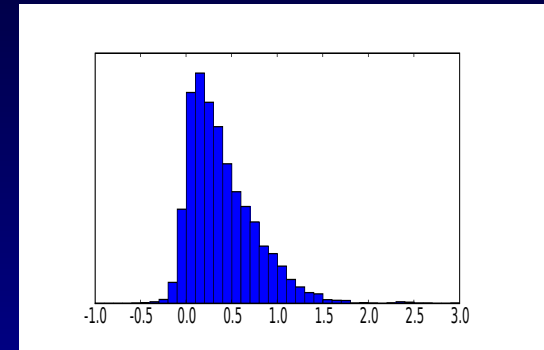
Histograms of Gradients

Objective: Investigate how well variability of surface slope is captured in SB and MB (8beam) observations



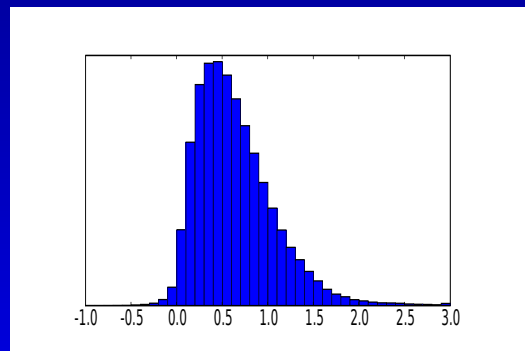
(A)

for MB data from Pinegl-Simul
DEM (max. slope 4.3°)



(B)

for SB data from Pinegl-Simul
DEM (max. slope 2.9°)



(C)

for entire Pinegl-Simul DEM.
(max. slope 4.9°)

Questions?



Conclusions Multi-Beam -2

(A) Multi-Beam or only Single-Beam Lidar for ICESat-2?

- (1) Multi-beam lidar observations will yield 3-dimensional information on land and sea ice elevation
- (2) Locally-known hi-res elevation captures gradient and directional derivative distribution of the entire surface to 99.9 percentile
- (3) Spatial statistical properties from swath data can be used to extrapolate between ground tracks

→ With a MB system, ICESat-2 can meet and advance the “Decadal Survey” objectives for cryospheric observation, change detection, modeling and prediction.

(B) Swath Mapper (16 Beams) — Split Beam (4 or 2 Beams)

(1) Swath Mapper

- (a) Achieves superior spatial resolution and hence better accuracy and more spatial information (as in (A)) (140m gradient fields, 0.85m along-track sampling)
- (b) More susceptible to cloud/ aerosol caused data loss, but studies so far indicate good spatial data collection
- (c) Instrument to date only tested on aircraft

(2) Split Beam

- (a) Twice the track density as SB, with 140m offset data in 2° rotated mode
- (b) Cannot derive gradient fields with 140m grids, but across-track slope locally, otherwise 4km gradient fields
- (c) Split-beam technology with pulse-repetition lidar with specs similar to GLAS